Techniques for measuring effectiveness of Water Sensitive Urban Design

Techniques pour mesurer l'efficacité de la conception urbaine respectueuse de l'eau

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RÉSUMÉ

La conception urbaine respectueuse de l'eau offre une alternative aux mesures traditionnelles d'assainissement pluvial. Elle vise à minimiser l'étendue des surfaces imperméables en milieu urbain et à reproduire autant que possible le cycle naturel des eaux de pluies grâce à des retenues d'eaux temporaires, au recyclage, et à la réutilisation des eaux pluviales. L'intégration de chemins de ruissellement dans les espaces verts, associée à d'autres techniques de conception urbaine respectueuse de l'eau, peut réduire la dimension des réseaux d'assainissement en zone urbaine. Ces techniques comprennent des bassins de rétention et de détention des eaux de pluie pour réduire les débits de pointe, des noues et fossés enherbés associés à des arbres et arbrisseaux qui facilitent l'infiltration des eaux et la filtration des polluants. La conception urbaine respectueuse de l'eau est très répandue en Australie, et de nombreuses municipalités optent pour cette technique de gestion des eaux pluviales. Cependant cette technique représente un coût de maintenance élevé, et l'un des enjeux est de pouvoir en démontrer l'efficacité. Ce papier vise à introduire un modèle hybride de qualité des eaux. Ce modèle qui comprend un modèle déterministe et un réseau de neurones artificiels (ANN) sera utilisé pour vérifier l'efficacité de l'aménagement du Parc de Connells Point (Connells Bay, Sydney, Australie).
Une approche novatrice a été utilisée, associant des paramètres calibrés de qualité des eaux et un réseau artificiel de neurones capable de prévoir la qualité des eaux émanant de l'aménagement effectué selon la technique de la conception urbaine respectueuse de l'eau. Le modèle hybride a été calibré et validé en utilisant des mesures de la qualité des eaux sur le site lors d'un événement pluvial important. Cette approche utilise les points forts des deux modèles et génère un outil d'aide à la décision fiable pour tester l'efficacité de différentes techniques de gestion intégrée des eaux de pluie.

ABSTRACT

Water sensitive urban design (WSUD) offers an alternative to the traditional conveyance approach to stormwater management. It seeks to minimise the extent of impervious surfaces and mitigate changes to the natural water balance, through on-site reuse of the water as well as through temporary storage. By integrating major and minor flow paths in the landscape and adopting a range of water sensitive design techniques, the size of the structural stormwater system required can be reduced. These techniques include detention and retention basins to lower peak flows, and grassed swales and vegetation to facilitate water infiltration and pollutant filtration.
WSUD has been widely adopted in Australia and is being implemented in varied local government areas. The major challenge to the success of WSUD is however its measure of effectiveness over the life cycle given that it demands high maintenance. The aim of this paper is to introduce a hybrid modelling approach that involves both deterministic model and Artificial Neural Network (ANN) for testing the effectiveness of water sensitive urban design at Connells Park Reserve, Connells Bay, Sydney, Australia. A novel approach has been used that allows a combination of calibrated water quality and neural based models to predict the water quality from WSUD. The models were calibrated and validated using water quality monitoring data for a significant storm event in the catchment. This approach takes the strength of both the modelling techniques in providing a decision support tool that can be used with confidence in testing the efficacy of stormwater treatment train for range of catchment conditions.

KEYWORDS

Water Sensitive Urban Design, Water Quality Modelling, Artificial Neural Networks

BACKGROUND

Water Sensitive Urban Design (WSUD) is an alternative approach to urban stormwater management that seeks to minimise the harmful effects on the surrounding environment using detention, retention, treatment and reuse of stormwater using naturalised systems as compared to conventional drainage. WSUD has been widely adopted in Australia and is being implemented in varied local government areas. The major challenge to the success of WSUD is however its measure of effectiveness over the life cycle given that it demands high maintenance. Water quality monitoring of WSUD is not cost effective and it only provides only a snapshot of treatment during the sampling regime whilst biological processes in naturalised treatment systems warrant long term continuous monitoring to gauge effectiveness of treatment. The conventional approach is to calibrate water quality models to observed sampling data and use the models for predicting long term effectiveness of WSUD. Most of the deterministic water quality models used for urban stormwater management are limited by the modelled treatment process and it is difficult to replicate water quality in storm events on continuous basis.

The aim of this paper is to introduce a hybrid modelling approach that involves both deterministic model and Artificial Neural Network (ANN) for testing the effectiveness of water sensitive urban design at Connells Park Reserve, Connells Bay, Sydney, Australia. A novel approach has been used that allows a combination of water quality and neural based models to predict water quality from WSUD. The models were calibrated and validated using water quality monitoring data for a number of significant storm events in the catchment. This approach takes the strength of both the modelling techniques in providing a decision support tool that can be used with confidence in testing the efficacy of stormwater treatment train for range of catchment conditions.

1 WATER SENSITIVE URBAN DESIGN

Connells Point is located in the South Eastern part of Sydney, Australia and is part of Kogarah Municipal Council local government area. Council constructed a stormwater treatment system based on the principles of Water Sensitive Urban Design (WSUD) in 2005 to mitigate flood impacts and improve water quality in the bay. The design incorporated underground stormwater treatment system that conveys and treats stormwater up to tertiary level and mimics the natural drainage of the area. The treatment train comprises of Gross Pollutant Trap (GPT) as primary treatment, low flows upto tertiary treatment (6 month Average Recurrence interval, ARI) through bio-retention trench and surcharge of high flows through the nature reserve from two surcharge pits (see Figure 1).

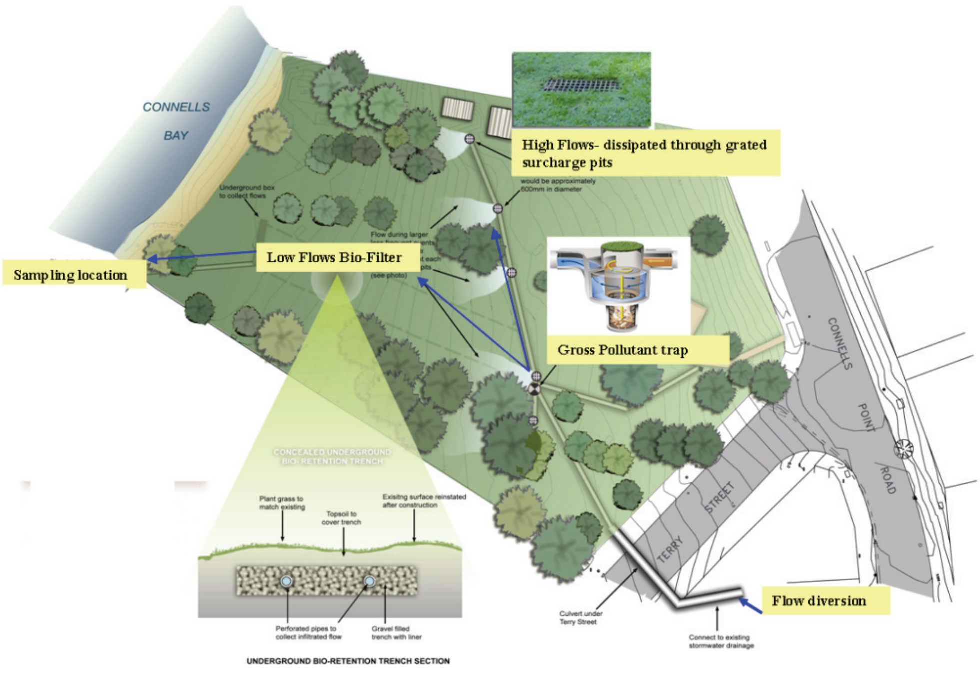


Figure 1 Water Sensitive Urban Design for Stormwater treatment

The unique approach in design is the separation of low and medium flows through stormwater outlet and dissipation of high flows through the Connells Point Reserve. Low flows were treated in the bio-retention trench (0.69 m^3/s, 6 month ARI storm event), Medium flows upto 1 year ARI were conveyed through a unique bypass arrangement within the bio-retention trench consisting of Atlantis matrix cells, High flows, upto 20 year ARI (2.5 m^3/sec) were dissipated through two surcharge pits within the reserve. The treatment train under consideration comprises the following:

1.1 Gross Pollutant trap (GPT)

CDS vortex gross pollutant separation devices by CDS technologies, Australia were used at Connells Point. CDS Gross Pollutant Traps are an offline treatment unit with an offline storage sump. The offline treatment function ensures that the flows to be treated are only the flows entering the screening chamber of the unit. During periods of high flows in excess of the design flows, water overflows the fixed weir in the diversion chamber preventing disturbance and re-suspension of material already trapped in the sump. CDS Gross Pollutant Traps are effective in removing gross pollutants and coarse particles greater than 2 microns (Matthai, 2000).

1.2 Bio-retention trench

A bio-retention trench (also called bio-filter) is a shallow, excavated trench filled with gravel or sand lined with geotextile fabric into which stormwater runoff drains. Stormwater enters the trench and undergoes a filtration process where particulates and some dissolved pollutants are retained in the trench and then the treated runoff the exfiltrates from the trench (URS, 2004).

Bio-retention systems generally provide the following functions as highlighted in URS (2004). Removing sediments and attached pollutants by filtering through surface vegetation, ground cover and underlying filter media, and delaying runoff peaks by providing retention capacity and reducing flow velocities. The size and grading of the gravel was determined to achieve the desired removal efficiency of pollutants. The entire trench was filled with coarse sand with grading D_{10} 2mm and D_{90} of 5 mm (10% larger than 5 mm and 10% smaller than 2mm) and the entire trench was covered in geotextile. The flows were dissipated through series of slotted subsoil drains wrapped in geotextile within the trench.

1.3 Design Approach

Water Quality Models are used widely to design and test the performance of stormwater treatment train. The design for water quality through the stormwater treatment was achieved using the Model for Urban Stormwater Improvement Conceptualisation, MUSIC developed by the Cooperative Research Centre for Catchment Hydrology, Australia (MUSIC 2005). MUSIC model was created to be an aid to decision making by predicting stormwater quality (nutrients, suspended solids) and quantity for a variety of user input scenarios.

The MUSIC Model calculates stormwater quality and runoff through algorithms based on known performance characteristics of common stormwater quality improvement measures. MUSIC uses a simple pollutant generation algorithm that uses stochastic generation of pollutants based on user inputs of event mean concentration and standard deviations in storm and base flows. MUSIC can model a variety of treatment measures, either in series or parallel to form a treatment train and runs on an event or continuous basis (6 mins to 24 hour time steps) enabling short and long-term analysis. MUSIC is currently used widely in Australia for design and regulatory compliance by agencies, council and consultants.

The capacity of MUSIC to model on an event basis allows the designer to revisit the model after the adopted solution has been constructed and compare water quality samples collected on-site to those predicted in the model. The design of Connells Park Reserve WSUD was tested during the design stage using MUSIC model to comply with water quality requirements set out by the regulatory authorities.

2 WATER QUALITY MONITORING

A monitoring program was established to monitor the water quality post construction of the stormwater treatment system in 2005. To test the effectiveness of treatment system, on site monitoring was conducted at the outlet from bio-retention trench near the bay for storm events 15th-16th October 2006. The storm events were significant for the catchment with intensity upto 1 year ARI.

Sampling of the inflows to the stormwater treatment train was not feasible due to site constraints. The inflows were not found to be critical as the bio-filters convey the first flush with inlets lower than surcharge points from the GPT and therefore always run upto the design capacity in storm events. Also, due to access issues no sampling could be conducted at the upstream and downstream of the

GPT sections of the treatment train. With these restrictions, sampling could only be conducted at the outlet of the treatment train. All sampling was conducted during wet weather events. A total of 48 samples were collected every 15 minutes for storm event lasting upto 12 hours duration. A number of heavy metals and organic matter in the treated water were also analysed, but only the design parameters are discussed. The adopted sampling methodology for this project with respect to calibration of the computer models involved collecting grab samples at the outlet of the treatment train.

The results of sampling are given in Table 1. Based on the Australian and New Zealand Environment and Conservation Council (ANZECC, 2000) guidelines, the following trigger values were identified (see Table 1) as applicable to the Connells Point catchment.

Pollutant	Maximum	Minimum	Median	ANZECC Trigger Value
pH	7.16	7.02	7.1	Lower Trigger Value - 6.5 Upper Trigger Value - 8.0
Total Phosphorus, mg/L	0.09	0.02	0.04	
Total Nitrogen, mg/L	1.02	0.5	0.73	
Turbidity (NTU)	3.4	1.67	2.9	Trigger value between 6 and 50 NTU
Total Suspended solids, mg/L	4.0	1.1	2.1	

Table 1 Sampling Results and Trigger Values for water quality monitoring

The analysed samples indicate values for both pH and turbidity to be well below trigger values identified and the majority of heavy metals tested were in concentrations below testing capabilities.

3 METHODOLOGY FOR EVALUATING EFFECTIVENESS OF WSUD

The major challenge to the success of Water Sensitive Urban Design (WSUD) is its measure of effectiveness over the life cycle given that it demands high maintenance. To measure the effectiveness requires comprehensive water quality observations both upstream and downstream of the treatment train to test for range of inflow conditions. In this study, water quality observations and flows upstream could not be monitored due to site constraints but were not found to be critical for developing neural based models.

The water quality sampling for this study involved using automatic samplers at outlet that trigger with rain events as the manual sampling was restricted by access and timing of storm events. This is an expensive option given that large amount of data samples are required for such testing and not all events can be monitored to gauge the long-term effectiveness of the treatment devices.

The methodology presented in this paper is based on using a limited water quality sampling data based on representative storm events and calibrating water quality models (MUSIC) over a range of inflow conditions observed during the sampling period. The difficulty in calibration of water quality models is inherent in the water quality processes modelled and the use of these models as tool for measuring effectiveness is therefore limited. A novel approach has been used that allows a combination of calibrated water quality and neural based models to predict the water quality from WSUD. This approach takes the strength of both the modelling techniques in providing a decision support tool that can be used with confidence in testing the efficacy of stormwater treatment train for range of catchment conditions.

The methodology involves the following steps:-

Stage 1 This involved calibrating the MUSIC model to the observed sampling data (48 samples) by fine tuning the hydrological parameters and pollutant generation rates. It is pertinent to note that no flow calibration could be achieved due to absence of flow monitoring data. However, attempt was made to match the range of recorded water quality data since the objective was to gauge the effectiveness and not the treatment in terms of annual loads. This stage therefore involved calibrating the water quality variables to the observed field data.

Stage 2 This involved generation of time series of calibrated model for inflows, outflows and concentration of water quality parameters in and out of bio-retention trench. The time series were extracted for range of wet and dry weather conditions for testing by Artificial Neural Network (ANN) models.

Stage 3 This involved training of the neural network models using time series of input and output parameters from MUSIC models. The input parameters were modelled inflows, TSS, TP and TN whilst output parameters were recorded TSS, TP and TN. The trained model was then tested and validated using the modelled input and output parameters and best model was then adopted.

Stage 4 This involved running the trained and tested neural model for the modelled inflows and outflow parameters over the whole range of dry and wet weather conditions. This was called the production dataset and the results were then used to test the treatment effectiveness of the stormwater treatment train.

3.1 Calibrated MUSIC Model Results:

The results from calibrated MUSIC model are presented below. The results of modelled total suspended solids in the stormwater treatment train are presented in the Figure 2 below. The results show a good match between the recorded and the modelled total suspended solids over the range of recorded data in the storm events.

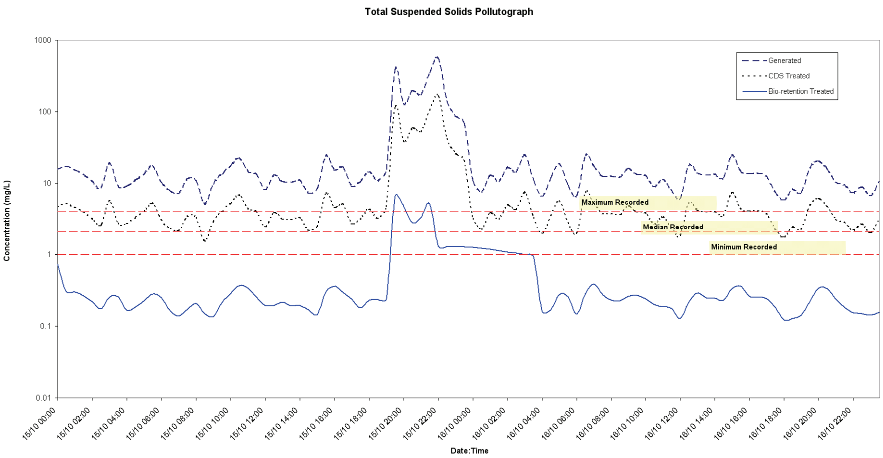


Figure 2 Modelled Total Suspended Solids Pollutograph

The results of total phosphorus (Figure 3) show a good match over the range of recorded data for the storm events. There is significant reduction in phosphorus for the storm events (around 74-89 %). This corroborates the assumption that phosphorus is mainly sourced from organic fraction in the catchment loads. The results of total nitrogen (Figure 4) show a good match with the range of recorded data for the storm events. The reduction of TN is not that significant in the treatment train (56-70%), the reduced treatment is expected as the bio-filter can only remove TN to limited extent.

3.2 Comments on MUSIC model

MUSIC model has got the following limitations:

- The modelling approach for hydrology is fairly simplistic in that it doesn't involve catchment slope, width etc., and, as a result, effects arising as a result of time of concentration of the catchment will be more noticeable in the more sophisticated models like EPA SWMM. Note no flow calibration has been attempted in this exercise.
- Pollutant export rates are based on Australian Runoff Quality (ARQ 2005). A standard approach has been followed for generation of pollutants based on methodology in MUSIC model (MUSIC 2005)
- The CDS Gross pollutant trap performance is based on simplistic treatment expression based on % removal rates that has been supplied by manufacturer. A 70% removal of TSS, 30% removal of TP was assumed in this modelling exercise, this could not be validated due to absence of water quality monitoring data downstream of the GPT.
- The removal through bio-filtration is based on simplistic model. The pollutant removal process through the soil filter is a function of both detention time as well as particle size. An increased level of pollutant removal is seen with increasing detention time and reduction in particle size. The expressions used could not be tested due to absence of water quality monitoring data upstream of bio-filter.

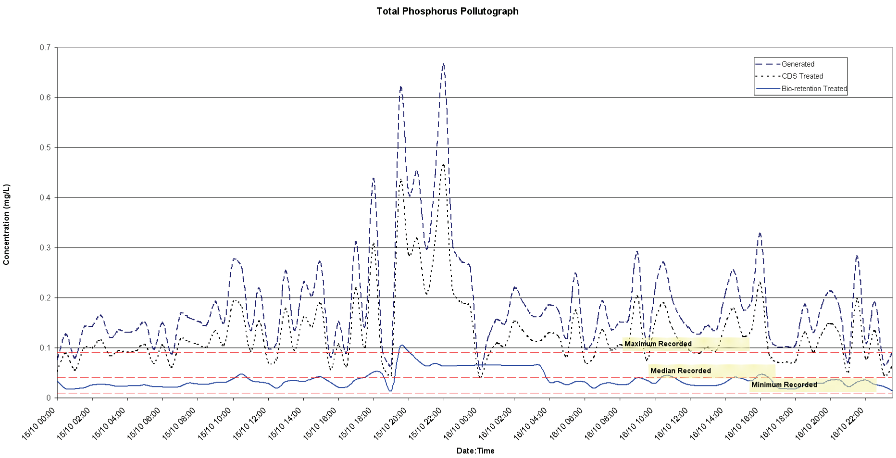


Figure 3 Modelled Total Phosphorus Pollutograph

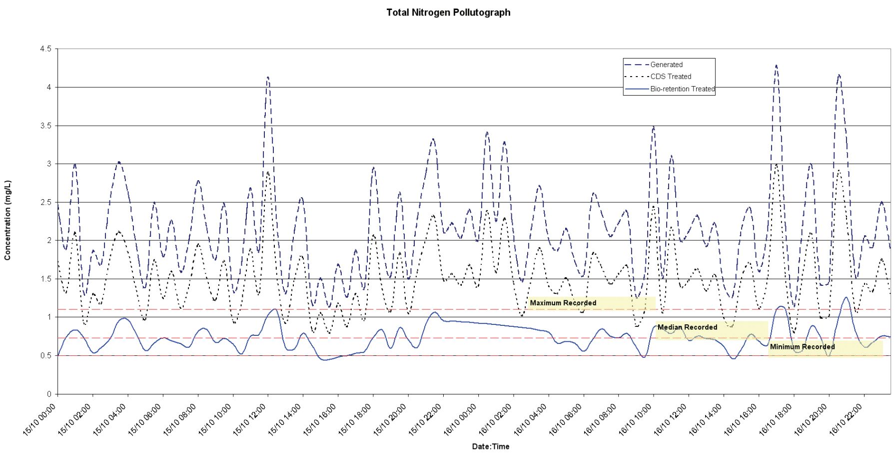


Figure 4 Modelled Total Nitrogen Pollutograph

Despite the above limitations the results from attempted calibration show a good approximation of the recorded water quality parameters and can be used with some confidence in using the modelled data for development of Artificial Neural Network (ANN) models.

4 ARTIFICIAL NEURAL NETWORK MODEL

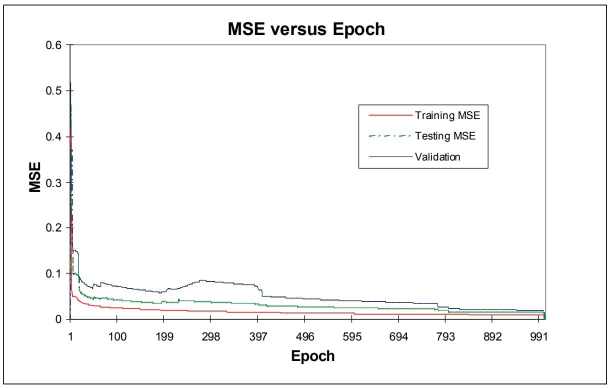
The purpose of this exercise was to predict water quality using Artificial Neural Network (ANN). A neural network is an adaptable system that can learn relationships through repeated presentation of data and is capable of generalizing to new, previously unseen data. Some networks are supervised, in that a human determines what the network should learn from the data. In this case, you give the network a set of inputs and corresponding desired outputs, and the network tries to learn the input-output relationship by adapting its free parameters. Other networks are unsupervised, in that the way they organize information is hard-coded into their architecture.

Neural network is a powerful data modelling tool that is able to capture and represent complex input/output relationships. The use of ANN is growing rapidly with successful applications in many areas including process control, engineering design, financial trading, credit evaluation, medical diagnosis, and cognitive simulation. This method has been also widely applied in prediction of runoff and water quality in water engineering (Refer Lek et al., Poff et al., 1996).

Neural network model was developed using neural network toolbox in MATLAB (Hines,1997). Input and output variables used were flows, TSS, TP and TN from MUSIC model runs. Also recorded data on TSS, TN and TP was used for validation of the ANN model.

A single hidden-layer feedforward neural network using back-propagation learning algorithms was developed with a detailed analysis of model design of those factors affecting successful implementation of the model. All features of a feedforward neural model were investigated including training set creation, number and layers of neurons, neural activation functions, and back-propagation algorithms. Least-squares regression was used to compare model predictions with test data sets. Most of the model configurations offered excellent predictive capabilities. Using either the logistic or the hyperbolic tangent neural activation function did not significantly affect predicted results. This was also true for the two learning algorithms tested, the Levenberg-Marquardt and Polak-Ribiere conjugate-gradient descent methods. The most important step during model development and training was the representative selection of data records for training of the model.

One fourth of the total data was selected for training, one fourth for validation (observed data) and the remaining one half for testing. Network performance was estimated by linear regression between the actual and target (predicted) water quality parameters after post-processing the output to the original scalar variables. The results of training, testing and validation are presented in the Figure 5 below. The figure shows that for trained network a Mean Square Error of 0.05 was achieved in just 40 epochs with convergence around 200 epochs. The results show a good convergence in 1000 epochs for all the datasets and this trained model was then used for the production runs (ie. predicted ANN model output for a time series of modelled input variables from MUSIC).



Best Network	Training	Testing	Validation
Epoch	1000	1000	1000
Minimum MSE#	0.0098	0.0148	0.0195
Final MSE#	0.0098	0.0148	0.0195

#Mean Square error

Figure 5 Results for trained Neural Network

The results of production runs for TSS, TN and TP are presented in Figures 6-8 below. Note the modelled ANN predicted output shows a better variability with the stormflow inflow data compared to that modelled in MUSIC. The linear regression of the observed TSS and predicted TSS is shown in Figure 9 below. It can be seen that the MUSIC model output is poorly correlated with the observed, this are due to inherent assumptions in the process modelled (ie. removal of suspended solids within the bio-filtration unit). ANN tends to remove this deficiency by developing a relationship between influent and outflow suspended solids which is independent of process and therefore proves to be better in predicting the observed dataset. It is to be noted that the predicted removal from CDS unit upstream of bio-filter is more deterministic (70% assumed based on data provided by manufacturers), therefore using MUSIC input for running ANN models is realistic and is proven by better match with the observed effluent dataset.

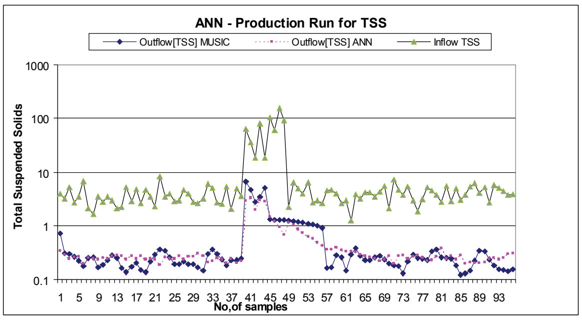


Figure 6 Time Series of predicted output from ANN model for TSS compared with MUSIC

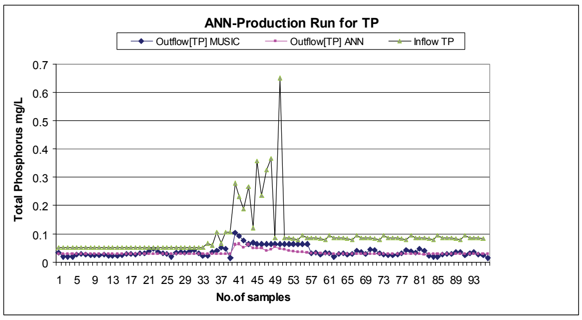


Figure 7 Time Series of predicted output from ANN model for TP compared with MUSIC

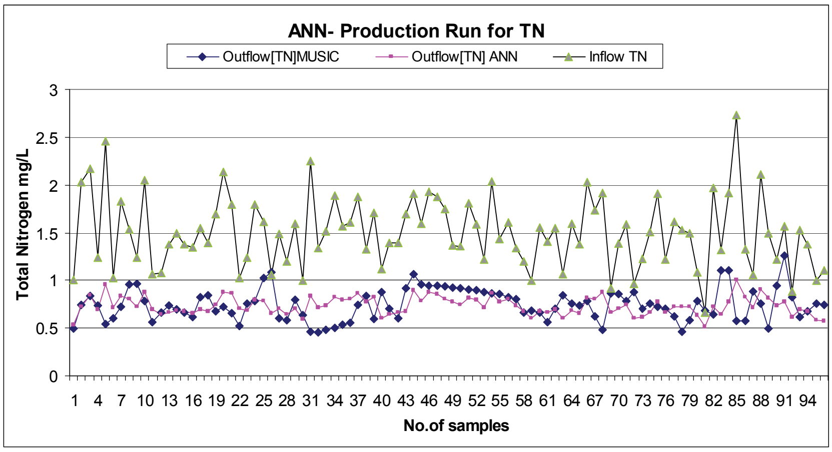


Figure 8 Time Series of predicted output from ANN model for TN compared with MUSIC

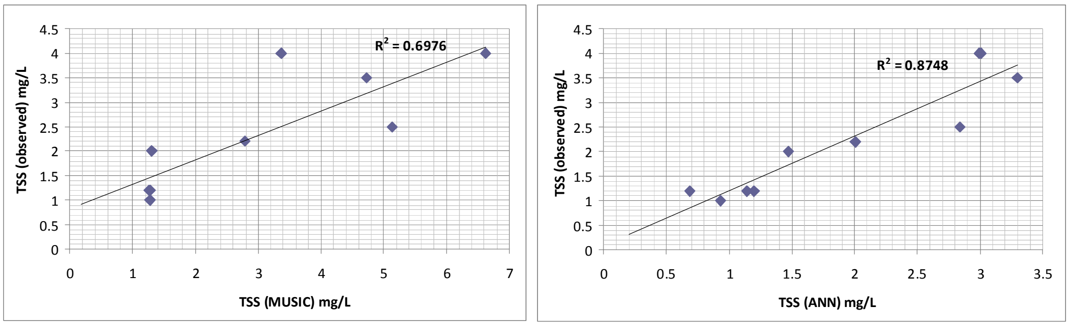


Figure 9 Linear Regression of the observed TSS and predicted TSS from the neural network

The linear regression of the observed TP and predicted TP is shown in Figure 10 below. It can be seen that the MUSIC model output is poorly correlated with the observed, this are due to issues with the deterministic model used for removal of TP in the bio-filter. ANN predicted output shows a better correlation with the observed. It is also to noted that the predicted removal from CDS unit upstream of bio-filter is more deterministic (30% assumed removal of TP based on manufacturer's recommendations) and hence shows a better correlation of ANN (that is derived from input pattern) with the recorded data.

The linear regression of the observed TN and predicted TN is shown in Figure 11 below. It can be seen that both MUSIC model and ANN output is poorly correlated with the observed, although ANN is better correlated compared with MUSIC. A possible explanation of this is no removal of TN assumed from the CDS unit upstream. As there is no manufacturer's data available for TN removal in CDS this could not be used in this exercise, but it will be worth testing this for future studies and better correlation of this model. Also, the results show that the removal process for TN is not well defined in the MUSIC model and has significant limitations. The results however show the strengths of using a hybrid modelling approach where strengths of both deterministic and neural based models can be used for prediction of water quality in a treatment system.

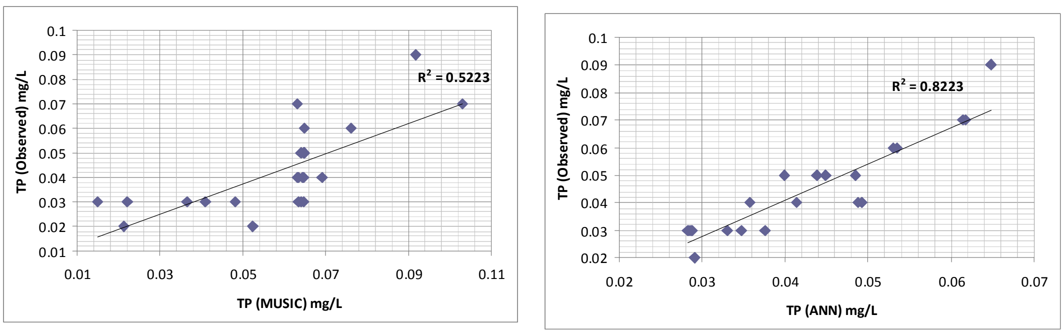
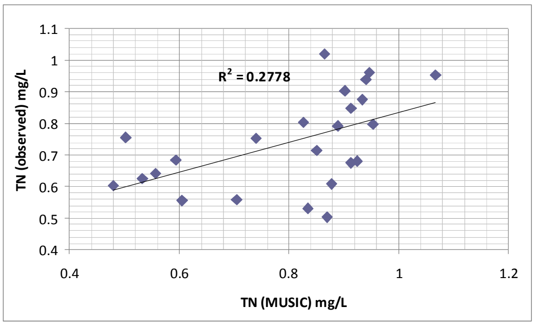


Figure 10 Linear Regression of the observed TP and predicted TP from the neural network



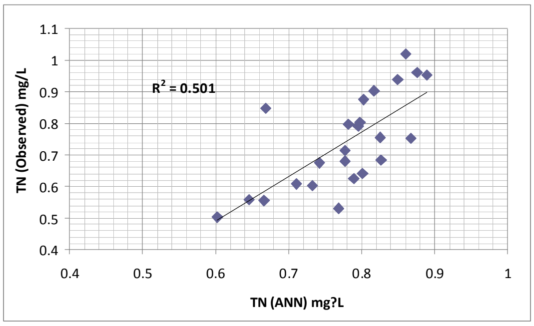


Figure 11 Linear Regression of the observed TN and predicted TN from the neural network

5 RESULTS

The results from both modelling approaches are presented in Table 2 below. The table shows a good match of ANN output versus MUSIC output compared with the recorded data for the storm events. All the variables are within the expected range from field data observed in biofiltration systems.

	Minimum	Median	Maximum
Total Suspended Solids (Observed)*	1.10	2.05	4.0
Total Suspended Solids (MUSIC)	0.18	1.16	6.62
Total Suspended Solids (ANN)	0.20	1.73	3.30
Total Phosphorus (Observed)	0.02	0.04	0.09
Total Phosphorus (MUSIC)	0.01	0.06	0.10
Total Phosphorus (ANN)	0.03	0.04	0.06
Total Nitrogen (Observed)	0.50	0.73	1.02
Total Nitrogen (MUSIC)	0.48	0.87	1.07
Total Nitrogen (ANN)	0.52	0.79	0.89

*Note: observed TSS data tabulated only for recordings above the detectable limits

Table 2 Results from ANN and MUSIC models compared with recorded data

The effectiveness of stormwater treatment train is shown in Table 3 below. It is to be noted that upto 99% removal of TSS, 89% removal of TP and 65% removal of TN is achieved in the treatment train. This is based on the generated pollutants into the treatment train; however reasonable match of ANN model output with recorded data gives confidence in the determination of these pollutants in the inflow stream. A major outcome of this exercise shows the limitations of MUSIC model in modelling the processes in the bio-filter system for removal of nutrients. A more sophisticated deterministic model (for eg., EPA SWMM) may improve the results of this hybrid modelling exercise.

The results were also tested for compliance with a regulatory criteria used in Australia which is based on meeting a water quality standard with criteria set based on percentiles. For this test exercise, a criteria set in two states, Victoria and Queensland were combined to test a worst case scenario for measuring effectiveness of the stormwater treatment train. This criterion has been achieved for all the parameters listed in Table 4 below. Results show that WSUD has achieved the water quality objectives set out in the design and surpasses all relevant statutory guidelines for discharge into the bay.

	Event Mean Concentration, mg/L	Potential removal, MUSIC model	Potential removal, ANN model
Total Suspended Solids	160	96-99%	98-99%
Total Phosphorus	0.25	59-94%	74-89%
Total Nitrogen	2.0	47-76%	56-70%

Table 3 Effectiveness of Stormwater Treatment Train

	Target Concentration mg/L	Criteria, frequency of compliance	ANN Results Target Concentration mg/L	Target achieved
Total Suspended Solids	15	50% of time	1.73	Yes
Total Nitrogen	0.6	100% of time	0.52	Yes
Total Phosphorus	0.05	100% of time	0.03	Yes

Table 4 Compliance with regulatory criteria

6 DISCUSSIONS

The hybrid modelling approach using both deterministic and artificial neural network models has demonstrated this as a powerful tool for evaluation of effectiveness of WSUD. The methodology adopted compliments the limitations of both the approaches and provides decision support tool that can be used with confidence. It is also cost effective as it does not involve extensive monitoring data to validate the effectiveness of constructed stormwater treatment train.

There are limitations with this modelling approach, however this is an area of further research and better deterministic models combined with other data mining techniques viz. genetic programming can provide more robust tools for measuring the treatment effectiveness of WSUD.

Based on results from hybrid modelling it can be concluded that the water quality at the outfall has surpassed all relevant statutory standards for discharge to the bay. It is anticipated that reduction of nutrient and sediment loads will provide habitat for flora and fauna in Connells Bay that will improve the recreational value of the area. This project has reached its objectives through good design development, community and stakeholder consultation, project management and innovative construction of stormwater treatment system.

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